14235

Classification of car in lane using support vector machines

Michael Del Rose, David Gorsich, Robert Karlsen

Tank Automotive Research, Development, and Engineering Center, Warren, MI 48397

ABSTRACT

Support Vector Machines (SVMs) have become popular due to their accuracy in classifying sparse data sets. Their computational time can be virtually independent of the size of the feature vector. SVMs have been shown to out perform other learning machines on many data sets. In this paper, we use SVMs to detect a car in a lane of traffic. Digital pictures of various driving situations are used. The results from the SVM algorithm are compared to results from a standard neural network approach.

Keywords: Support vector machines, neural network, image processing, pattern recognition

1. INTRODUCTION

Support vector machines (SVMs) are wide margin classifies that solve a quadratic programming problem to find the maximum separation between classes[1-4]. The algorithm is applied to the Tank Automotive Research, Development, and Engineering Center (TARDEC) car/lane image set. The image set was obtained using a digital camera mounted on a vehicle dash. The images are composed of views of either a clear road ahead or a car in front of the camera at various distances. A simulation experiment is performed to determine how well SVMs can do in warning a driver when a vehicle is in front of the car. The SVM results are compared with results from a standard neural network approach.

Section 2 describes the different methods used to process the images to find a good feature vector. Section 3 gives the results of the study. Section 4 describes other methods that might warrant further investigation into solving this problem. For detailed information on SVMs or neural networks, the reader is advised to consult the references.

2. IMAGE PRE-PROCESSING METHODS

Various techniques were investigated to find a feature vector that described the data set. Methods such as wavelets, masks, and histograms were explored with some having success and others not. This section describes the thoughts behind the investigation and the results that the methods gave.

Data was collected using several different digital cameras mounted on the dash of various cars. The images were colored with sizes ranging from 1280x1024 to 640x512. Pictures were taken of common road surfaces (dirt, highway, freeway, etc.) with either cars at different distances or no cars. Before processing, each image was converted to grayscale and resized using the nearest neighbor algorithm[5] to a standard size. The investigation into creating a good feature vector was centered on finding edges of the cars. Unfortunately, isolating the edges around the car turned out to be difficult due to other objects in the pictures having more prominent features.

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE **30 JUN 2000**	2. REPORT TYPE **Journal Article**	3. DATES COVERED **17-04-2000 to 23-05-2000**

4. TITLE AND SUBTITLE **Classification of car in lane using support vector machines**	5a. CONTRACT NUMBER
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S) **Michael Del Rose; David Gorsich; Robert Karlsen**	5d. PROJECT NUMBER
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **U.S. Army TARDEC,6501 East Eleven Mile Rd,Warren,Mi,48397-5000**	8. PERFORMING ORGANIZATION REPORT NUMBER **#14235**
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) **U.S. Army TARDEC, 6501 East Eleven Mile Rd, Warren, Mi, 48397-5000**	10. SPONSOR/MONITOR'S ACRONYM(S) **TARDEC**
	11. SPONSOR/MONITOR'S REPORT NUMBER(S) **#14235**

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

13. SUPPLEMENTARY NOTES

14. ABSTRACT
Support Vector Machines (SVMs) have become popular due to their accuracy in classifying sparse data sets. Their computational time can be virtually independent of the size of the feature vector. SVMs have been shown to out perform other learning machines on many data sets. In this paper, we use SVMs to detect a car in a lane of traffic. Digital pictures of various driving situations are used. The results from the SVM algorithm are compared to results from a standard neural network approach.

15. SUBJECT TERMS
Support vector machines, neural network, image processing, pattern recognition

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**Public Release**	**7**	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

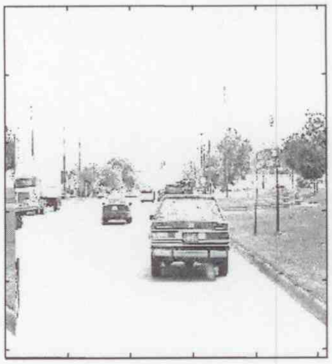

Figure 1a - Image

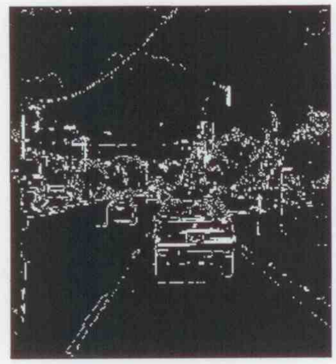

Figure 1b - Sobel mask with threshold = .2

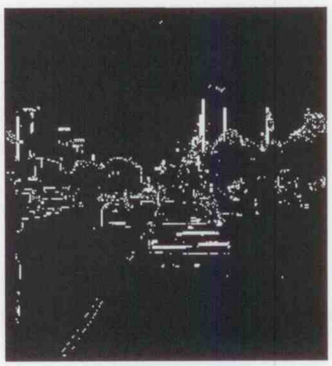

Figure 1c - Sobel mask with threshold = .4

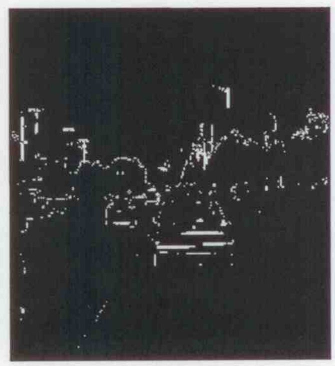

Figure 1d - Sobel mask with threshold = .6

Figure 1 - original image grayed and resized (a). Sobel mask taken of images and thresholded (b, c, d).

Figure 1a is an example of a typical grayscale image. A Sobel mask[5-7] is applied and the results are thresholded to find the edges (Figures 1b – 1d). Figure 1 shows that increasing the threshold results in decreasing the edges of the car. To reduce noise in the image without losing too much of the car outline, another algorithm must be used.

Applying the wavelet transform[8-10] to the image (or the edges of the image) works well if the intent is to use the approximation from the wavelet transform to resize it. However, local statistics from the wavelet transform (such as mean and energy) do not increase the classification rate. Instead, a look at the data shows that the center region is the place where there is a car (for pictures that had cars). We can reduce the image by cutting out the middle 128x128 section. Doing so reduces the unwanted edges caused by background objects. However, this method often cuts out edges of vehicles that are too close or off-center.

Another processing technique that was investigated was to use different size boxes around the center, called the box-in-box method[11]. Box sizes were 16x16, 32x32, 64x64, 128x128, and 256x256. These boxes

contained the Sobel edges of the image in that region. The goal was to encompass the full car outline while reducing the added noise of the edges due to the background. Each box represented a distance the car was away from the camera (for images with cars). A number of boxes were trained (on both car and no car images) and tested. If one of the boxes showed that a car outline was present then the classifier classified the image as having a car in front. Unfortunately, this method did not classify well due to different car styles, patches or glares in the roads, off-centered cars, bridges, etc.

The final feature vector was developed using a few of the techniques described above, along with an algorithm to find horizontal lines[12]. Since the edges of each car are not consistent with one another, a new way to view the images needed to be looked at. The car edges contain a number of horizontal lines coming from the bumper, rear window, top, bottom, etc. When looking at edges in no car images, the horizon and tree lines also produced horizontal lines, so they had to be sectioned off.

A Sobel mask was applied to find the edges in the center 128x128 area of the images. After this, an algorithm was applied to find consecutive horizontal pixels at least 6 pixels in length. Examples of the processing are shown in Figure 2 (for a car) and Figure 3 (for no car).

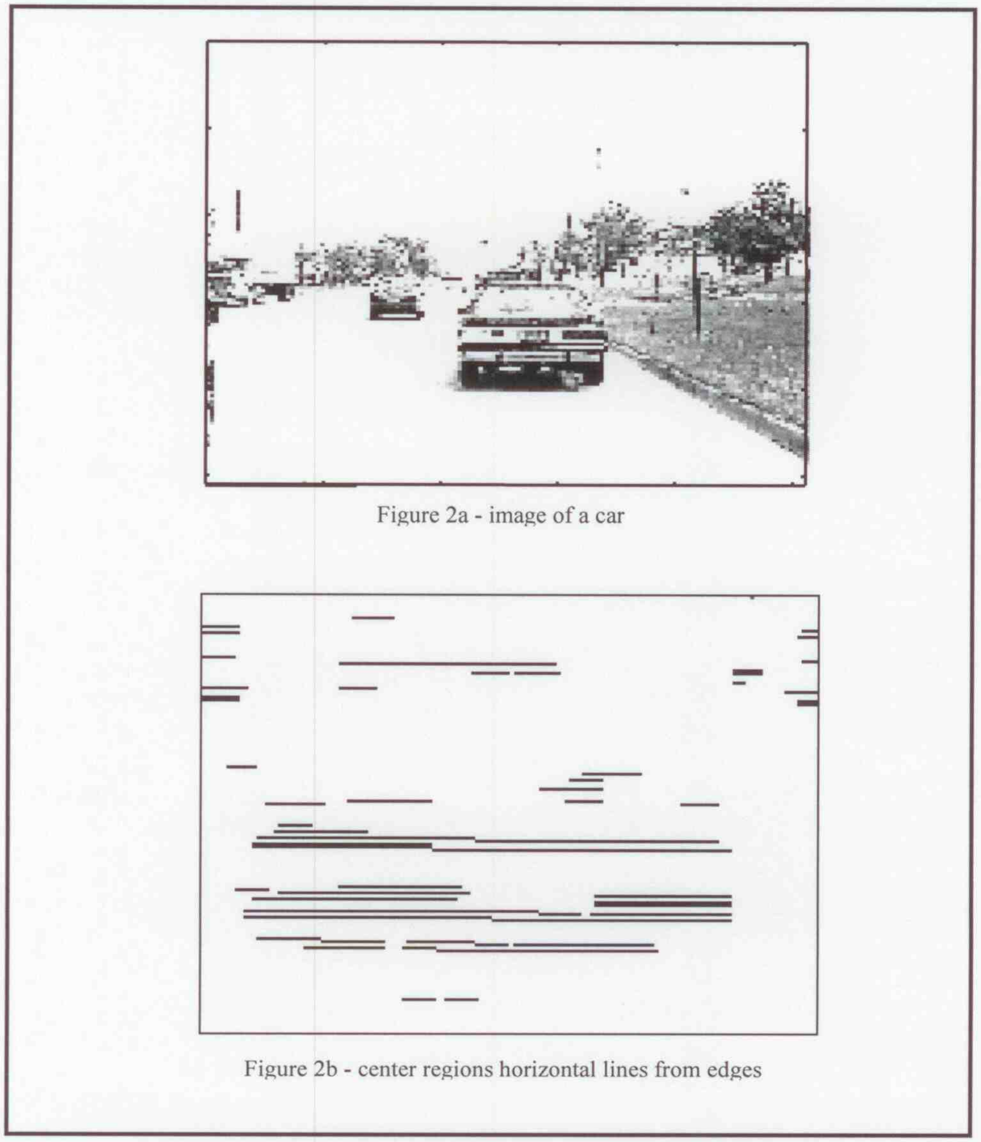

Figure 2a - image of a car

Figure 2b - center regions horizontal lines from edges

Figure 2 - image of a car (a) and the center horizontal lines (b)

Figure 3a - image of no car

Figure 3b - center regions horizontal lines from edges.

Figure 3 - Image of no car (a) and the center regions horizontal lines (b)

From this, the length of the lines were grouped (based on the number of consecutive pixels) and a histogram was formed[12]. The line groups were 6-8, 9-11, 12-14, 15-17, 18-20, 21+. These six numbers along with the total number of horizontal lines (at least 6 pixels long) were used as the final feature vector.

3. RESULTS

There were a total of 218 images with 89 car images and 129 no car images. Each image was represented by seven elements (see above). The feature data was split up into training and test vectors and put into a support vector machine (SVM)[3] and a standard neural network (NN)[13]. The SVM used a quadratic polynomial kernel. The NN has two layers with the hidden layer having either three or five neurons and the outer layer having one neuron. The activation function for all neurons is a unipolar sigmoid function. The results are shown in the Tables 1 and 2 below:

Trained 50 car and 50 no car:

SVM - poly 2 kernel	Classified as a car	Classified as no car
Actual Car	38	1
Actual No Car	4	75

Table 1a

NN – 3 hidden layer neurons	Classified as a car	Classified as no car
Actual Car	38	1
Actual No Car	6	73

Table1b

NN – 5 hidden layer neurons	Classified as a car	Classified as no car
Actual Car	38	1
Actual No Car	6	73

Table1c

Table 1 – SVM and NN classification matrix for 100 training samples

Calculating the classification rate for the SVM of Table 1a, we see that it chooses the correct class 95.8% of the time. Both NNs are the same with a classification rate of 94.9% (see Tables 1b and 1c). For Table 2, the number of training vectors increased from 50 per class to 64 per class. The results show that the SVM classification rate increased to 96.7%. The NN classification rates were 93.3% and 94.4% for the three and five neuron networks, respectively.

Trained 64 car and 64 no car:

SVM - poly 2 kernel	Classified as a car	Classified as no car
Actual Car	23	2
Actual No Car	1	64

Table 1a

NN – 3 hidden layer neurons	Classified as a car	Classified as no car
Actual Car	23	2
Actual No Car	3	62

Table1b

NN – 5 hidden layer neurons	Classified as a car	Classified as no car
Actual Car	23	2
Actual No Car	4	61

Table1c

Table 2 – SVM and NN classification matrix for 128 training samples

The results from this study have shown an example of SVMs outperforming NN with a small data set. The SVM classification rates were slightly higher then the NNs rates for 100 training samples. The SVMs classification rate increased as the number of training samples increased. However, the NNs classification rates stayed the same or decreased as the training samples increased.

4. FURTHER STUDY

Using histograms of groups of horizontal lines seems to tell us that something is in the path of the vehicle. Problems will arise if the vehicle's roll position is different then the one taking the pictures; horizontal lines will not be horizontal. A method to find parallel lines rather than horizontal lines should be employed. Using templates is another idea that could prove fruitful if it were to be used with the box-in-box method. The templates would be used for training (at different distances) and the images would be used for testing. Other paths of investigation should include better algorithms for denoising the data. The goal would be to remove all edges but that of the car. Unfortunately, the car is not always the most prominent feature in the image.

REFERENCES

1. B. Scholkopf, C. Burges, A. Smola, *Advances in Kernel Methods*, MIT Press, Cambridge, 1999.
2. V. Vapnik, *Statistical Learning Theory*, John Wiley and Sons, New York, 1998.
3. S. Gunn, *Support Vector Machines for Classification and Regression*, Technical Report, Image Speech and Intelligent Systems Group, Univ. of Southhampton, 1998.
4. R. Karlsen, D. Gorsich, G. Gerhart, "Target Classification Via Support Vector Machines," *Optical Engineering*, **39**:704-711, 2000.
5. H. Burdick, *Digital Imaging, Theory and Application*, McGraw-Hill, New York, 1997.
6. G. Baxes, *Digital Image Processing, Principles and Applications*, John Wiley and Sons, New York, 1994.
7. R. Crane, *A Simplified Approach to Image Processing*, Prentice Hall, Upper Saddle River, 1997.
8. G. Strang, T. Nguyen, *Wavelets and Filter Banks*, Wellesley-Cambridge Press, Wellesley, 1997.
9. R. Rao, A. Bopardikar, *Wavelets Transforms, Introduction to Theory and Applications*, Addison-Wesley, Reading, 1998.
10. M. Del Rose, *A Wavelet Processing Method for Signals*, Technical Report, University of Michigan, 1999.
11. M. Del Rose, *Image Processing Methods*, Technical Report, University Of Michigan, 1999.
12. M. Del Rose, *Hand Written Character Recognition*, Masters Thesis, University of Michigan, 2000.
13. C. Bishop, *Neural Networks for Pattern Recognition*, Oxford University Press, New York, 1995.